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THE ENVIRONMENTAL PERFORMANCE OF POLLUTING PLANTS: A SPATIAL ANALYSIS*

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ABSTRACT: This paper uses plant-level EPA and Census data to examine spatial factors affecting environmental performance, as measured by air pollutant emissions and regulatory compliance. We find significant effects for compliance, but not for emissions. Compliance is positively spatially correlated, partly explained by spatial correlations in observed plant characteristics, suggesting influences of industry agglomeration. The use of spatial econometric methods shows only small effects of spatially lagged compliance status, and does not greatly change the estimated contributions of other spatially explicit factors. Regulatory activity has the expected effect of increasing environmental performance, both at the inspected plant and at neighboring plants, but only for plants in the same state, demonstrating the importance of jurisdictional boundaries.

1. INTRODUCTION

This paper examines the determinants of environmental performance at a sample of U.S. manufacturing plants, concentrating especially on spatial factors. Differences in environmental performance across plants could be driven by differences in plant-specific characteristics (age, size, production technology), firm-specific characteristics (size, profitability, corporate culture), or external pressures (regulatory stringency, enforcement intensity, or lobbying pressures

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from neighborhood environmental groups). Environmental performance could be spatially correlated, with nearby plants having similar performance, if it is driven by location-specific external pressures: plants in the same state facing the same regulatory agency or plants in the same neighborhood facing the same environmental group. Spatial correlation could also result from endogenous interactions in plant behavior, such as "demonstration effects," where one plant's high compliance rate pressures neighboring plants to raise their own compliance rates.

Spatial correlation can be important in its own right, if it results in the concentration of poor performance among sets of nearby plants, creating local "hot spots." If hot spots are sufficiently damaging, social welfare might be improved by negative spatial correlations, where poor performers are balanced out by good performers in the same neighborhood. A less optimistic view of regulatory policy would point to concerns about environmental justice, with plants in less politically connected neighborhoods receiving less regulatory attention, resulting in local concentrations of poor environmental performance.

Spatial correlation could also bias the results of studies that fail to control for the spatial effects. For example, industry agglomeration could generate a "selection effect," whereby plants that cluster together for production-side reasons also tend to have similar environmental performance. These local similarities in performance could be mistakenly identified as the "treatment effect" of a location-specific factor such as regulatory stringency. Spatial econometric analyses can avoid such biases by testing for correlations in the explanatory variables and by controlling for the impact of neighboring plants' behavior.

There exists a substantial body of research examining the determinants of environmental performance, as measured by air pollution emissions and compliance. Compliance status is examined by Gray and Deily (1996), Gray and Shadbegian (2005), and Nadeau (1997), while emissions have been studied by researchers including Kahn (1999), Shadbegian and Gray (2003), and Gray and Shadbegian (2004).[1] This research most often focuses on *specific* deterrence, which is the direct impact of enforcement activity, i.e., the impact of an inspection on future compliance at the plant being inspected. In contrast, fewer studies have examined *general* deterrence, which occurs when an inspection affects compliance at other plants, by raising those plants' expectations of the amount of enforcement they will face in the future.

Spatial factors play a role in many of the variables used in these studies, although none have used spatial econometric models. The measures of regulatory enforcement are inherently spatial: differences across plants in regulatory activity depend on differences in enforcement stringency across regulatory agencies and nearby plants tend to face the same regulator. Jurisdictional boundaries provide another potentially important spatial factor connected with

[1]Studies on water pollution include Magat and Viscusi (1990), Laplante and Rilstone (1996), Helland (1998), Shimshack and Ward (2005), Sigman (2002, 2004), and Gray and Shadbegian (2004).

regulation, if regulators pay less attention to plants near the border, whose pollution primarily affects people in the next jurisdiction. The importance of these border effects is examined by Kahn (1999), Sigman (2002, 2004), and Helland (2003). Finally, the political clout of the population surrounding the plant may influence regulatory activity; measures of political activity and population demographics have been examined by Hamilton (1993, 1995), Arora and Cason (1999), and Gray and Shadbegian (2004).

Our analysis incorporates spatially based information in three new ways. First, in addition to the usual demographic and political information about those living near the plant, we construct a measure of regulatory activity at nearby plants that distinguishes between plants in the same state and plants in different states, allowing us to test for general deterrence effects and to test whether those deterrence effects end at jurisdictional borders. Second, we test for spatial correlations in the explanatory variables, in the performance measures, and in the residuals from non-spatial models. Comparing the magnitudes of these correlations allows us to see whether spatial correlations in plant characteristics (possibly driven by industry-agglomeration effects) contribute to correlations in environmental performance. Finally, we use spatial econometric techniques to allow explicitly for correlations with the performance of nearby plants, to see whether (and how much) omitted spatial effects bias the results of non-spatial models.

Our results indicate a significant role for spatial factors in environmental performance, without seriously biasing the effects of other factors. Compliance status is positively correlated at nearby plants in the same state, but this correlation does not carry across state borders. The residuals from a compliance model show weaker spatial correlations, so spatial correlations in explanatory variables can explain a sizable part (but not all) of the correlation in compliance across nearby plants. In spatial econometric models we find that spatially lagged compliance terms are small and usually not significant, confirming that the explanatory variables capture most of the spatial effects. Our analyses of air pollution emissions, for both conventional and toxic pollutants, show no evidence of spatial correlations — in fact few variables in our model show significant impacts on air pollutant emissions, perhaps due to the smaller sample sizes involved or due to the heterogeneity of the plants included in our sample (in order to obtain sufficient numbers of nearby plants for the spatial econometric analysis, we include all manufacturing plants, not just those from a single industry as most prior research has done).

Much of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, and more pollution-abatement-intensive plants having lower compliance rates. Local demographic characteristics matter — having more elderly or minority residents nearby is associated with greater compliance — but political activity has little impact. We find the expected effects of regulatory enforcement (although not always significant): more inspections at the plant, at nearby plants, and at all other plants in the state, are associated with greater compliance. The latter two results demonstrate the importance of general deterrence effects. Inspections at nearby plants in other states do not seem to increase compliance, showing a significantly different effect from inspections at nearby plants in the same state, and reinforcing the message that jurisdictional borders matter.

Section 2 presents a model of spatial correlations in environmental performance. Section 3 describes the data used in the analysis, including possible spatial characteristics of the regulatory variables. Section 4 discusses issues relating to spatial econometrics that are important for estimating our models. Section 5 presents the results, and Section 6 concludes.

2. SPATIAL CORRELATIONS IN ENVIRONMENTAL PERFORMANCE

As Manski (2000) observes, it can be difficult to distinguish among three reasons for correlations in outcomes within a group: endogenous interactions, contextual interactions, and correlated effects. In our case, these three reasons correspond to a plant's environmental performance being influenced by the actual performance of nearby plants, being influenced by other (exogenous) characteristics of nearby plants, and only appearing to be influenced by nearby plants' performance — the latter case arising if neighboring plants share similar unmeasured characteristics influencing their performance, leading to similarities in performance across neighboring plants without a direct causal link. All three cases could result in positive spatial correlations in performance, and the spatial econometric techniques we use in this research help focus our attention on the different ways in which neighboring plants are related.

To better understand the reasons for such spatial correlations, we begin with a basic model of environmental performance. Consider an individual manufacturing plant[2] seeking to maximize profits while facing benefits and costs associated with a given level of environmental performance (EP). We abstract from the production side of the plant's decision, represented in Equation (1) by a base level of profits Π_0, and focus on the relative magnitudes of the compliance costs associated with achieving a particular level of EP and the penalty from regulatory agencies predicted for a plant with that level of EP

$$\Pi(EP, Xcc, Xpen) = \Pi_0 - CompCost(EP, Xcc) - Penalty(EP, Xpen) \tag{1}$$

with $\partial CompCost/\partial EP > 0$ and $\partial Penalty/\partial EP < 0$. A profit-maximizing plant will balance the marginal costs of improved performance with the marginal benefits — recognizing that the benefits of increased EP come in the form of lower penalties

$$\partial CompCost/\partial EP = -\partial Penalty/\partial EP \tag{2}$$

[2]We speak of profit-maximizing plants, rather than firms, since all of our analysis is done at the plant level.

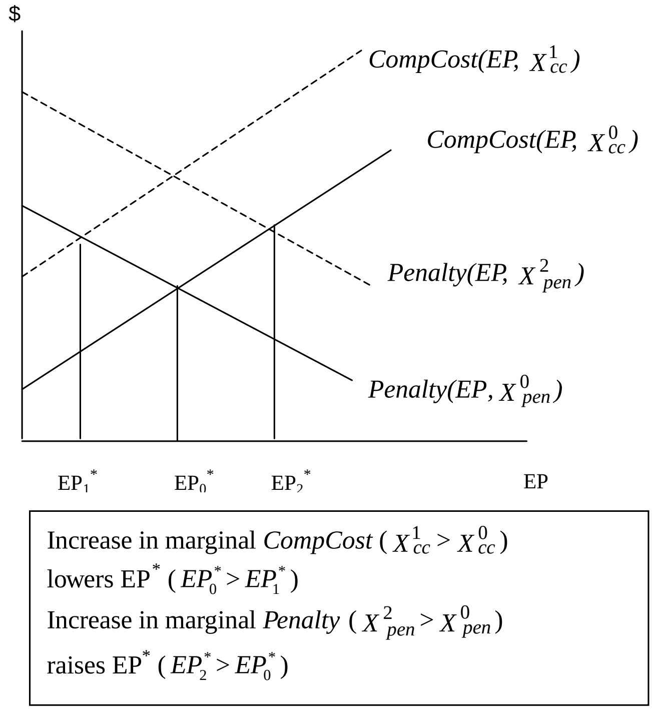

FIGURE 1: Impact of Shifts in *Xcc*, *Xpen* on Optimal Performance EP^*.

Xcc and *Xpen* in Equation (1) are characteristics of the plant or the plant's environment that increase the marginal costs (or marginal penalties) associated with any given level of EP, so $\partial^2 CompCost / \partial EP \partial Xcc > 0$ and $\partial^2 Penalty / \partial EP \partial Xpen < 0$. *Xcc* variables include plant characteristics that affect the costs of achieving a given level of EP (its size, age, production technology, managerial ability, etc); *Xpen* variables include the expected level of environmental regulatory activity faced by the plant (raising the likelihood that a poorly performing plant will be caught), and the stringency of that regulation (raising the dollar penalty that will be imposed if the plant is caught). Not all *Xpen* variables need to be tied to characteristics of the regulatory agency; the demographics and politics of the surrounding population may also matter. Plants surrounded by politically active and environmentally concerned neighbors could face a higher *Xpen* due to those neighbors' ability to intervene in the environmental permitting process to punish plants with low EP.

Figure 1 shows the impact of changes in *Xcc* and *Xpen* on the optimal level of performance, EP^*, working through Equation (2). If cost-related factors increase from X^0cc to X^1cc then EP^* decreases from EP_0^* to EP_1^*. On the other hand, if benefit-related factors increase from X^0pen to X^2pen then EP^* increases from EP_0^* to EP_2^*. Note that a single factor could affect both *Xcc* and *Xpen*.

For example, if regulations are grandfathered, older plants may face less strict regulations (*Xpen* decreases), but may also find it more costly to achieve a given level of performance (*Xcc* increases), with both effects tending to reduce EP^* at older plants.[3]

In this model, spatial correlation could arise for a variety of reasons. First, the factors that drive environmental performance could themselves be spatially correlated. These correlations arise automatically in the construction of many of our explanatory variables: plants in the same neighborhood are necessarily surrounded by the same demographic factors; nearby plants are usually regulated by the same agency. Spatial correlation in other explanatory variables may be more subtle, with plant characteristics such as age and size exhibiting spatial correlation when similar plants tend to cluster together due to agglomeration effects as found in Henderson (1999). Some unmeasured factors that influence performance may also have a spatial component, such as an especially active neighborhood environmental group, which could drive similarities in the residual (unexplained) performance at neighboring plants.

Spatial effects could also occur in regulatory pressures. Some states might have more aggressive regulatory agencies, doing more inspections and imposing more penalties throughout the state (Gray and Deily, 1996). At a more local level, the locations of regulatory offices may influence regulatory intensity if facilities near the office are more frequently inspected. Spatially defined enforcement variables may help us test broader regulatory issues, such as decomposing the impact of inspections into general and specific deterrence. We would expect that plants would be more attentive to inspections at nearby plants (rather than distant ones) when forming predictions about the local stringency of enforcement. This can be tested by comparing the impacts of local- and state-level enforcement activity. The fact that most regulatory activity is done by state regulatory agencies also provides a spatially defined consistency check: inspections at nearby plants in other states should be irrelevant.

Finally, a purely spatial component of the model can arise if the environmental performance at one plant is directly related to the performance at nearby plants. For example, one plant with especially good performance could have a demonstration effect (showing that good performance is possible), putting more pressure on neighboring plants to perform well. Regulators might also have preferences related to the spatial pattern of environmental performance, though the sign of this effect is unclear — a desire to avoid hot spots would lead to negative spatial correlations while a desire to push all polluters away from politically active areas towards less favored areas could lead to positive correlations (the latter effect being at the heart of the literature on environmental justice).

[3]Note that this is based on measuring EP in terms of emissions performance. If we measure EP in terms of regulatory compliance, the less stringent regulations due to grandfathering could make older plants more likely to be in compliance than younger ones, even if the older plants' emissions performance is worse.

3. DATA DESCRIPTION

Our analysis uses cross-sectional data on environmental performance in 1997 for 521 manufacturing plants, located within 50 miles of the centers of three US cities. These cities are all near state borders, providing us with many adjacent plants, some in different states, allowing us to test for differences in regulatory impacts and spatial correlations across jurisdictional boundaries. The cities (and states) involved are St. Louis (Missouri and Illinois), Cincinnati (Ohio, Kentucky, and Indiana), and Charlotte (North and South Carolina). We gathered data for all plants located within 50 miles of any of the cities from EPA databases. Plant location information (latitude and longitude) came from EPA's Envirofacts database, taken from the Permit Compliance System and the Toxic Release Inventory modules. The final sample of 521 plants came from a merger of plant-level Census microdata and EPA data that required plants to have both Census and EPA data, including air pollution compliance information for 1997. We use two sub-samples of the 521 plants for further analyses: 299 of these plants have data on releases of toxic air pollutants, while 102 of these plants have air pollution emissions data for conventional pollutants, particulates and sulfur dioxide.[4]

Our research was carried out at the Census Bureau's Boston Research Data Center, using confidential plant-level databases developed by the Census's Center for Economic Studies. The primary Census data source is the Longitudinal Research Database (LRD), which contains information on individual manufacturing plants from the Census of Manufactures and Annual Survey of Manufacturers [for a more detailed description of the LRD data, see McGuckin and Pascoe (1988)]. From the LRD we extracted information for 1997, originally collected in the 1997 Census of Manufactures. We use the plant's total value of shipments (TVS) as a direct measure of the plant's size, deflated and in log form (SIZE), as well as to scale many of the other variables in this study including the emissions-based dependent variables. Our control for plant age (AGE) is the plant's age in 1997 (1997 — year of birth).[5] We control for the plant's efficiency using labor productivity (LPROD) measured as real output per employee. Finally a dummy variable (SINGLE) identifies plants which are owned by single-plant firms (firms which own no other manufacturing plants).

In addition to these Census variables taken directly from the LRD, we use the Census Bureau's annual Pollution Abatement Costs and Expenditures (PACE) survey. The PACE survey data include annual plant-level pollution abatement operating cost data from 1979 to 1994. Since the survey was not carried out in 1997, we use the plant's abatement operating costs from 1991 to 1994, and divide this by the plant's shipments in those years to get a

[4]The scope of the sample we created for this project was limited by the considerable effort required to gather, merge, and clean the multiple EPA and Census datasets needed for the analysis.

[5]We would like to thank John Haltiwanger for providing the plant age information, which was calculated based on Census data.

measure of the pollution abatement expenditure intensity at the plant, PAOC, as a percentage of total costs.[6]

Our regulatory measures come from EPA databases. From the Integrated Data for Enforcement Analysis (IDEA) database we obtain a quarterly history of the plant's air pollution compliance status. Our compliance measure, COMPLY, is a dummy variable, indicating whether the plant was in compliance throughout the year (if a plant was out of compliance in any quarter, COMPLY was set to zero).[7] To measure air pollution enforcement activity, we use information from the Envirofacts database to construct INSPECT, the total number of "inspection-type" actions (e.g., inspections, emissions monitoring, stack tests) directed towards this plant during the 1993–1995 period. We create INSPNB by summing INSPECT over all manufacturing plants within 10 miles, and INSPNBOUT as the part of INSPNB contributed by plants located in other states. For a state-level measure of overall regulatory activity, STACT, we calculate the average number of regulatory actions in 1997 per plant in the entire state.

We obtain data on air pollution emissions from EPA's 1996 Emissions Inventory database (the closest available year to 1997, since the Inventory is done on a three-year cycle). The Emissions Inventory database provides information on the tons of emissions per year for criteria air pollutants, of which we consider particulates under 2.5 microns ($PM_{2.5}$) and sulfur dioxide (SO_2).[8] These variables have been scaled by the plant's total value of shipments in 1997, so they represent pollution intensity (tons of pollution per million dollars of shipments). The EPA's 1997 Toxic Release Inventory (TRI) provides information on releases of toxic pollutants into the air (AIRTOX) for all manufacturing facilities with sufficiently large use and/or emissions of toxic substances, which we also express in intensity terms.

We use demographic information at the block group level from the 1990 Census of Population (as compiled by Geolytics, Inc., in their CensusCD data) to measure the characteristics of the population near each plant (taking all block groups with centroids within 10 miles of the plant as the relevant population). The health of some people, such as the old and the very young, is more sensitive to air pollution, which should lead a "socially optimizing" regulator to put more pressure on nearby plants to improve their environmental performance. We measure these groups by ELDERS, the fraction of the population 65 or older, and KIDS, the fraction of the population under 6. For "Environmental Justice" reasons we might expect plants located in poor and minority neighborhoods to

[6] We imputed PAOC based on published four-digit industry data for those plants which were not in the PACE survey.

[7] There are several different codes for compliance status in the EPA data, but only one or two of the noncompliance codes are at all frequent, so it was not practical to construct a multinomial measure of compliance. We follow EPA's categorization of which codes refer to noncompliance.

[8] We also analyzed emissions of nitrogen oxides, finding results similar to those for sulfur dioxide.

face less pressure to improve environmental performance.[9] We measure this with POOR, the fraction of the population living below the poverty line, and MINORITY, the fraction of the population that is nonwhite.

We use information at the county level to characterize the political climate surrounding the plant. TURNOUT is the fraction of registered voters in the county who voted in the 1992 Presidential election. DEMOCRAT is the fraction of voters in the county voting for the Democratic presidential candidate in 1992. ENVSPEND is the percentage of the budgets of all local governments within the county that is spent on environmental amenities such as parks and recreation. All three of these variables are expected to raise a plant's environmental performance, since they are associated with politically active, liberal, and pro-environmental populations being around the plant.

Finally, we calculate whether a plant is within 10 miles of a state border, represented with a dummy variable BORDER. Regulators might feel less political pressure to strictly regulate a plant when some of the negative impact from its pollution is affecting residents of another state. Previous research by Gray and Shadbegian (2004) finds evidence of a border effect — plants located near state borders emit more air pollution.

4. SPATIAL ECONOMETRIC METHODS

Based on the earlier discussion (and Figure 1), we expect a plant's environmental performance to depend on a set of factors that shift the plant's marginal compliance cost and expected penalty

$$EP_i^* = \alpha + \beta * Xcc_i + \delta * Xpen_i + e_i \tag{3}$$

The coefficients on the *Xcc* variables are expected to be negative, while those on the *Xpen* variables should be positive, noting the earlier caveat that some factors (e.g., plant age) could shift both curves.

As described in Anselin (1988), spatial econometrics incorporates information about the spatial orientation of data points into traditional economic models. Spatial dependence can arise in a model in two ways: spatial dependence of the error terms and structural spatial dependencies of the dependent variable (these two types are sometimes called spatial error models and spatial lag models, respectively). The former effect can occur when spatially correlated explanatory variables are omitted from the model. If these omitted variables are unrelated to the variables included in the model, OLS will yield unbiased yet inefficient estimates, since it ignores the correlation of the error terms. We can correct for spatial error effects by modifying the error term from

[9]According to the Office of Environmental Justice at EPA, environmental justice exists when "no group of people, including racial, ethnic, or socioeconomic group, ... bear[s] a disproportionate share of the negative environmental consequences resulting from industrial, municipal, and commercial operations."

Equation (3)

$$e_i = \rho * W * e_i + u_i \tag{4}$$

W in Equation (4) is a weighting matrix that puts more weight on nearby observations, possibly also limited to similar observations (in our case, plants in the same state and/or industry). $W * e_i$ is therefore a spatially lagged error term, ρ is the autoregressive coefficient, and we assume $u \sim N\ (0, \sigma^2)$.

Structural spatial dependencies arise when the environmental performance of the plant is directly dependent on the performance of nearby plants, based on the behavior of plants or regulators as described above (demonstration effects for plants, hot spots, or environmental justice effects for regulators). We can account for structural spatial dependencies by augmenting Equation (3) as follows

$$EP_i^* = \alpha + \rho * W * EP_i^* + \beta * Xcci + \delta * Xpen_i + e_i \tag{5}$$

Here $W * EP_i^*$ is a spatially lagged dependent variable, ρ is the autoregressive coefficient, and we assume $e \sim N\ (0, \sigma^2)$. Note that structural spatial dependencies cause more problems than do spatially dependent errors: omitting the spatially lagged dependent variable can lead OLS to produce biased estimates and invalid statistical tests, through an omitted variable bias.

We begin our modeling by estimating non-spatial models, along the lines of Equation (3), to provide a baseline set of results for comparison with our spatial models. We then test for spatial correlation in the explanatory variables. Next we test for spatial correlation in the environmental performance variables and the residuals from the non-spatial models to see whether omitted factors might be driving spatial effects in performance, or whether the spatial effects are primarily due to structural spatial dependencies. Based on these results we decide whether to estimate a model with spatially correlated errors, as in Equation (4), or with structural spatial dependencies, as in Equation (5). Finally, we compare our spatial results with the results from the non-spatial models, to see how much they affect the estimated coefficients. We use the spatial econometrics library in the Econometrics Toolbox for MATLAB, as described in Lesage (1999) to perform all of our spatial econometric analyses.[10]

5. RESULTS

Table 1 presents summary statistics for the variables used in our analysis. Note that we actually have three samples of data, depending on the dependent variable in the analysis: 102 plants for emissions of conventional air pollutants, 299 plants for releases of toxic air pollutants, and all 521 plants for compliance with air pollution regulations. The explanatory variables are presented only for the full sample, but means for the sub-samples with emissions data[11] differ

[10]The toolbox is available at http://www.spatial-econometrics.com.

[11]Complete results available from authors.

TABLE 1: Descriptive Statistics (calculated for 521 observations in the compliance sample, except as noted)

Variable	Mean (s.d)	Description
Dependent variables		
COMPLY	0.891 (0.312)	Dummy variable = 1 if a plant is in compliance with air regulations in 1997
AIRTOX	1.238 (4.990)	(N = 299) TRI air emissions/shipments (tons/$000,000) in 1997
$PM_{2.5}$	0.360 (0.718)	(N = 102) Particulates emissions under 2.5 microns/ shipments (tons/$000,000) in 1996
SO_2	3.613 (17.933)	(N = 102) Sulfur dioxide emissions/shipments (tons/$000,000) in 1996
Inspection activity		
INSPECT	0.484 (0.742)	Number of plant inspections (1993–1995)
STACT	0.575 (0.222)	Average number of regulatory actions per plant in state (1997)
INSPNB	18.960 (18.056)	Total number of 1993–1995 inspections at all manufacturing plants within 10 miles
INSPNBOUT	2.019 (6.637)	Total number of 1993–1995 inspections at all manufacturing plants located within 10 miles of the plant, but located in a neighboring state
Plant characteristics		
SIZE	10.223 (1.520)	Log of real shipments in 1997
AGE	40.545 (18.536)	Age of the plant = 1997 – year plant was opened
LPROD	0.297 (0.386)	Log of real shipments/employment in 1997
PAOC	0.874 (1.388)	Pollution abatement operating costs/shipments (1991–1994 average)
DIRTYSIC	0.361 (0.481)	Dummy variable = 1 if a plant is in SIC 26, 28, 29, 33, or 34
Demographic variables		
POOR	10.894 (3.941)	Percentage of population within 10 miles living below the poverty line in 1990
ELDERS	11.882 (2.115)	Percentage of population within 10 miles 65 or older in 1990
MINORITY	18.622 (11.832)	Percentage of population within 10 miles nonwhite in 1990
KIDS	8.629 (0.730)	Percentage of population within 10 miles under the age of 6 in 1990
BORDER	0.390 (0.488)	Dummy variable = 1 if a plant is within 10 miles of a state border
ENVSPEND	1.947 (2.766)	Share of county local government spending on environmental amenities in 1992
DEMOCRAT	0.401 (0.107)	Fraction in the county voting for the Democratic candidate in 1992
TURNOUT	0.549 (0.069)	Fraction of registered voters in county voting in 1992 Presidential election

little from those calculated for the full sample — plants with emissions data are somewhat less likely to be in compliance with air regulations and have a history of receiving slightly more air inspections, although neither sample of plants is getting many inspections, with only 48 percent of the plants in the full sample receiving any air inspections during the 1993–1995 period.

We begin our analysis by examining the determinants of environmental performance without using spatial econometrics, as in Equation (3). Table 2 presents the determinants of compliance, using a Probit model due to the binary nature of the compliance variable. Most of the significant results are for plant characteristics. Plants that are larger, plants in dirty industries, plants with higher pollution abatement spending, and plants owned by single-plant firms are all significantly less likely to be in compliance.[12] The effects of plant age and productivity are not significant, though age has the expected sign (younger plants are more often in compliance). The demographics of the surrounding population show some of the expected effects, yet these effects are mostly insignificant: plants in neighborhoods with more elderly people or more young children have better performance, while plants in poor neighborhoods (and non-minority neighborhoods) have worse performance. These demographic results are similar to those in Gray and Shadbegian (2004), which also found minority effects contrary to those anticipated by environmental justice concerns. The political variables are also insignificant, although their signs are consistent across the models: plants located in counties which spend more on environmental activities, counties with higher voter turnout, and (surprisingly) counties with more Republican voting or near state borders, have higher compliance rates.

Model 2b contains two measures of regulatory activity, INSPECT and STACT. Both measures have the expected positive impact on compliance, indicating the presence of both specific (INSPECT) and general (STACT) deterrence effects, but neither is significant. Measures of general deterrence with more precise spatial definition, INSPNB and INSPNBOUT, are included in Model 2c, with the expected signs (and borderline significance). Inspections at nearby plants help increase compliance, but only if those plants are in the same state. We discuss these regulatory effects in more detail later, in the context of our spatial econometric models.

Table 3 presents the results for emissions of air pollutants, both toxic (AIRTOX) and conventional ($PM_{2.5}$, SO_2). As it happens, we do not find any evidence that air pollution enforcement reduces emissions — the only significant effect of regulatory activity is higher releases when nearby plants have been getting air pollution inspections (an unexpected result). The only explanatory variable with consistently strong effects is plant size, where larger plants show smaller emissions — but since emissions are calculated relative to plant size, and only plants with relatively large emissions are included in the EPA data, the SIZE

[12]The numerical coefficients for SINGLE could not be disclosed for confidentiality reasons. SINGLE is not included in our later analyses of emissions and toxic releases because those analyses contain very few single-plant firms.

TABLE 2: Non-Spatial Models of Compliance (*t*-statistics in parentheses)

DEPVAR	2a COMPLY	2b COMPLY	2c COMPLY
INSPECT		0.153	0.174
		(1.31)	(1.47)
INSPNB			0.013
			(1.65)
INSPNBOUT			−0.023
			(−1.49)
STACT		0.517	
		(0.82)	
LPROD	−0.014	0.009	−0.009
	(−0.06)	(0.04)	(−0.04)
AGE	−0.005	−0.005	−0.006
	(−1.13)	(−1.14)	(−1.38)
SIZE	−0.196	−0.203	−0.199
	(−2.85)	(−2.87)	(−2.81)
SINGLE	− −	− −	− −
DIRTYSIC	−0.437	−0.414	−0.447
	(−2.37)	(−2.20)	(−2.39)
PAOC	−0.129	−0.130	−0.123
	(−2.49)	(−2.47)	(−2.26)
POOR	−0.043	−0.025	−0.023
	(−1.16)	(−0.61)	(−0.61)
MINORITY	0.019	0.015	0.015
	(1.83)	(1.27)	(1.31)
ELDERS	0.113	0.118	0.113
	(1.82)	(1.88)	(1.82)
KIDS	0.052	0.104	0.112
	(0.37)	(0.68)	(0.78)
BORDER	0.067	0.066	0.047
	(0.33)	(0.33)	(0.23)
ENVSPEND	0.069	0.068	0.048
	(0.88)	(0.86)	(0.68)
DEMOCRAT	−0.569	−0.602	−1.628
	(−0.49)	(−0.51)	(−1.26)
TURNOUT	1.088	1.922	1.487
	(0.78)	(1.16)	(1.01)
R^2	0.130	0.138	0.146
Log-L	−156.47	−155.12	−153.69

Note: Estimates are based on observations of 521 plants in 1997, using a Probit analysis. Exact coefficients for SINGLE cannot be reported, due to Census disclosure rules; the table shows the sign and (when doubled) statistical significance at the 5 percent level.

TABLE 3: Non-Spatial Models of Air Emissions (*t*-Statistics in Parentheses)

DEPVAR	3a AIRTOX	3b AIRTOX	3c $PM_{2.5}$	3d $PM_{2.5}$	3e SO_2	3f SO_2
INSPECT	0.128	0.098	0.096	0.082	5.772	5.897
	(0.36)	(0.28)	(0.96)	(0.80)	(2.26)	(2.28)
INSPNB		0.061		−0.001		0.082
		(2.40)		(−0.10)		(0.32)
INSPNBOUT		−0.015		0.004		−0.149
		(−0.32)		(0.26)		(−0.36)
STACT	−1.274		−0.983		0.450	
	(−0.55)		(−1.24)		(0.02)	
AGE	0.010	0.006	0.011	0.011	0.060	0.057
	(0.70)	(0.39)	(2.84)	(2.86)	(0.64)	(0.58)
LPROD	1.010	1.000	0.021	0.073	1.031	1.084
	(1.29)	(1.28)	(0.09)	(0.33)	(0.18)	(0.19)
SIZE	−1.235	−1.181	−0.092	−0.099	−3.943	−3.924
	(−5.06)	(−4.88)	(−1.34)	(−1.43)	(−2.28)	(−2.26)
DIRTYSIC	−1.225	−1.213	−0.117	−0.048	−0.925	−0.956
	(−1.87)	(−1.88)	(−0.56)	(−0.24)	(−0.17)	(−0.18)
PAOC	−0.170	−0.129	0.016	0.016	−0.661	−0.670
	(−0.83)	(−0.63)	(0.17)	(0.17)	(−0.28)	(−0.28)
POOR	−0.086	0.002	−0.032	−0.026	0.203	0.210
	(−0.58)	(0.01)	(−0.79)	(−0.64)	(0.20)	(0.20)
MINORITY	0.044	−0.001	0.011	0.008	0.011	0.033
	(1.11)	(−0.04)	(1.11)	(0.71)	(0.04)	(0.12)
ELDERS	0.101	0.061	−0.007	−0.007	1.009	1.129
	(0.47)	(0.29)	(−0.11)	(−0.101)	(0.60)	(0.66)
KIDS	−0.235	0.058	−0.023	0.052	1.532	2.015
	(−0.42)	(0.11)	(−0.11)	(0.25)	(0.29)	(0.38)
BORDER	1.105	0.807	−0.245	−0.169	−1.331	−1.123
	(1.46)	(1.06)	(−1.08)	(−0.74)	(−0.23)	(−0.19)
ENVSPEND	−0.094	−0.119	−0.016	−0.001	−0.255	−0.288
	(−1.00)	(−1.26)	(−0.60)	(−0.04)	(−0.37)	(−0.45)
DEMOCRAT	−5.067	−8.926	0.455	1.908	2.681	3.889
	(−1.29)	(−2.11)	(0.25)	(1.29)	(0.06)	(0.10)
TURNOUT	4.800	5.624	−2.005	−1.225	−15.699	−10.381
	(0.86)	(1.25)	(−1.01)	(−0.61)	(−0.31)	(−0.20)
R^2	0.156	0.158	0.218	0.204	0.187	0.189

Note: Estimates are based on observations of 299 plants in 1997 for AIRTOX and 102 plants in 1996 for $PM_{2.5}$ and SO_2, using an ordinary least squares (OLS) analysis.

coefficients can hardly be treated as evidence for economies of scale in controlling emissions.

We now turn to spatially explicit analysis of the data. In Table 4 we examine the degree of spatial correlation in our data, using Moran's *I* test and three spatial weighting matrices. The first weighting matrix (INV) weights data from all the other plants near the same city by the inverse of the distance to those plants. The second weighting matrix (INV_ST) allows us to test for the importance of borders by using the same inverse distance weights but applying a zero weight to plants located in a different state. We also examine a third measure (INV_ST_SIC), which further restricts the weights to plants in both the same state and the same two-digit SIC industry (limited to the compliance models, where the sample size is sufficiently large).

Panel A shows the spatial correlations for our dependent variables, the measures of environmental performance. The only one that shows strong structural dependencies is compliance. A plant's compliance status tends to be positively correlated with the compliance status of nearby plants. The weighting matrix matters for this comparison — the spatial effects are much larger when we restrict our attention to plants in the same state (INV_ST), but are small and insignificant when we include plants in neighboring states. Restricting the weight matrix to only plants in the same industry and state (INV_ST_SIC) further increases the magnitude of the spatial correlation for compliance. Neither toxic nor conventional pollutant emissions show any significant evidence of spatial correlation; sulfur dioxide emissions show a (surprisingly) negative spatial correlation, but this is small and not significant.

Panel B shows the spatial correlations for the explanatory variables, all of which except INSPECT show positive spatial correlations.[13] Note that using a different spatial weighting matrix makes little difference in the estimated spatial correlation for any of the explanatory variables. On the whole, these results support the existence of agglomeration effects. Nearby plants tend to be similar plants, and this would be expected to generate spatial relationships in the environmental performance measures (though we only find such effects for compliance).

Panel C of Table 4 shows the spatial correlations for the residuals from the non-spatial models estimated earlier. Given the results in Panel A, it is not surprising that the residuals from the models of air pollutant emissions show uniformly insignificant spatial correlation. On the other hand, the compliance residuals continue to show positive spatial effects for those weighting matrices (INV_ST and INV_ST_SIC) where the earlier spatial effects were found. However, these residuals show smaller spatial correlations than the original compliance measures. These reductions are larger for model 2c, which accounts for local general deterrence with INSPNB and INSPNBOUT, than for model 2b, which uses the state-level measure of general deterrence, STACT. This suggests that part of the spatial correlation in COMPLY is being driven by spatially correlated explanatory variables — using the INV_ST weighting matrix, 35 percent of the spatial effects for compliance are explained by model 2b and an additional 18 percent (for a total of 53 percent) are explained by model 2c.[14]

[13]We do not calculate spatial correlations for the demographic (neighborhood-based) or political (county-based) variables, since they are spatially correlated by construction.

[14]Model 2b = (0.057–0.037)/0.057 = 35 percent; Model 2c = (0.057–0.027)/0.057 = 53 percent. For INV_ST_SIC the reductions are somewhat smaller: 27 percent and 41 percent, respectively.

TABLE 4: Moran's *I* Tests for Spatial Correlations (*p*-Values in Parentheses)

VARIABLE	#OBS	WEIGHT = INV	INV_ST	INV_ST_SIC
A: Dependent variables				
COMPLY	521	0.015 (0.109)	0.057 (0.000)	0.079 (0.013)
AIRTOX	299	0.005 (0.363)	0.011 (0.335)	
$PM_{2.5}$	102	0.003 (0.380)	0.006 (0.375)	
SO_2	102	−0.017 (0.394)	−0.017 (0.395)	
B: Explanatory variables				
INSPECT	521	0.007 (0.280)	0.009 (0.288)	0.012 (0.361)
LPROD	521	0.047 (0.000)	0.057 (0.000)	0.186 (0.000)
AGE	521	0.115 (0.000)	0.127 (0.000)	0.134 (0.000)
PAOC	521	0.045 (0.000)	0.045 (0.001)	0.152 (0.000)
SIZE	521	0.053 (0.000)	0.059 (0.000)	0.299 (0.000)
C: Residuals from Non-Spatial Models				
COMPLY(2b)	521	−0.003 (0.395)	0.037 (0.009)	0.058 (0.063)
COMPLY (2c)	521	−0.004 (0.392)	0.027 (0.047)	0.047 (0.114)
AIRTOX (3b)	299	−0.010 (0.360)	−0.001 (0.230)	
$PM_{2.5}$ (3d)	102	−0.028 (0.287)	−0.033 (0.311)	
SO_2 (3f)	102	−0.035 (0.333)	−0.037 (0.335)	

Notes: The calculations of the Moran's *I* test are done using three different spatial weighting matrices: INV = (1/distance), INV_ST = (1/distance) restricted to plants in the same state, and INV_ST_SIC = (1/distance) restricted to plants in the same state and in the same two-digit SIC industry. The model numbers for residuals in panel C refer to the models estimated in Tables 2 and 3.

Having found evidence of spatial correlations, at least for compliance, we now move to spatial econometric techniques that can explicitly control for these spatial effects. We are interested in the significance of the spatial terms, as well as any impact that their inclusion has on the estimated coefficients for other explanatory variables. As noted earlier, we could control for spatial correlation in the error terms (Equation 4) or for structural spatial dependencies (Equation 5). To choose between these methods, we return to the results in Table 4, comparing the magnitudes of the spatial correlation in the original environmental performance variables and the spatial correlation in the residuals from the non-spatial models. The correlations for the original compliance measure are substantially larger than those for the residuals, indicating that the structural spatial dependencies model is more appropriate [see Anselin and Rey (1991)]. Thus we choose to estimate Equation (5), including a spatially lagged dependent variable in the model.

Table 5 shows the results for our spatial models of compliance, using three variations on the spatial weighting matrix. We find a small positive impact of

TABLE 5: Spatially-Lagged Models of Compliance (p-Values in Parentheses)

	5a	5b	5c	5d	5e	5f
DEPVAR	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY
WEIGHT	INV	INV	INV_ST	INV_ST	INV_ST_SIC	INV_ST_SIC
RHO	0.010	0.008	0.015	0.009	−0.012	−0.019
	(0.092)	(0.192)	(0.033)	(0.157)	(0.303)	(0.182)
INSPECT	0.178	0.195	0.189	0.190	0.172	0.183
	(0.065)	(0.039)	(0.051)	(0.052)	(0.077)	(0.068)
INSPNB		0.007		0.005		0.015
		(0.168)		(0.301)		(0.022)
INSPNBOUT		−0.021		−0.014		−0.024
		(0.078)		(0.175)		(0.082)
STACT	0.170		−0.118		0.480	
	(0.398)		(0.422)		(0.246)	
LPROD	−0.001	0.032	0.030	0.015	0.021	0.033
	(0.496)	(0.441)	(0.470)	(0.500)	(0.458)	(0.467)
AGE	−0.005	−0.006	−0.005	−0.006	−0.005	−0.007
	(0.131)	(0.093)	(0.124)	(0.094)	(0.125)	(0.070)
SIZE	−0.205	−0.210	−0.212	−0.199	−0.224	−0.218
	(0.000)	(0.002)	(0.002)	(0.003)	(0.000)	(0.005)
SINGLE	− −	− −	− −	− −	− −	− −
DIRTYSIC	−0.451	−0.431	−0.473	−0.442	−0.448	−0.470
	(0.007)	(0.004)	(0.011)	(0.006)	(0.012)	(0.005)
PAOC	−0.135	−0.131	−0.131	−0.119	−0.133	−0.130
	(0.003)	(0.012)	(0.003)	(0.020)	(0.009)	(0.013)
POOR	−0.020	−0.012	−0.020	−0.009	−0.024	−0.022
	(0.286)	(0.370)	(0.307)	(0.386)	(0.288)	(0.278)
MINORITY	0.012	0.014	0.013	0.012	0.013	0.015
	(0.135)	(0.107)	(0.119)	(0.152)	(0.133)	(0.085)
ELDERS	0.111	0.118	0.109	0.114	0.120	0.120
	(0.040)	(0.040)	(0.027)	(0.025)	(0.039)	(0.042)
KIDS	0.104	0.132	0.096	0.141	0.098	0.115
	(0.252)	(0.172)	(0.257)	(0.141)	(0.248)	(0.216)
BORDER	0.087	0.064	0.061	0.052	0.084	0.064
	(0.358)	(0.379)	(0.384)	(0.399)	(0.356)	(0.379)
ENVSPEND	0.078	0.065	0.062	0.082	0.135	0.075
	(0.106)	(0.113)	(0.114)	(0.087)	(0.064)	(0.131)
DEMOCRAT	−1.291	−1.760	−1.167	−1.538	−0.675	−1.901
	(0.135)	(0.081)	(0.165)	(0.089)	(0.304)	(0.074)
TURNOUT	1.888	1.672	1.676	1.556	1.680	1.346
	(0.119)	(0.122)	(0.157)	(0.140)	(0.191)	(0.169)

Note: These estimates are based on observations of 521 plants in 1997, using a Bayesian spatial Probit analysis, as described in LeSage (2000). RHO is the estimated autoregressive coefficient, as in Equation (5). The analyses are done using three different spatial weighting matrices: INV = (1/distance), INV_ST = (1/distance) restricted to plants in the same state, and INV_ST_SIC = (1/distance) restricted to plants in the same state and the same two-digit SIC industry. Exact coefficients for SINGLE cannot be reported, due to Census disclosure rules; the table shows the sign and (when doubled) statistical significance at the 5 percent level.

RHO, the spatially lagged compliance of nearby plants, significant in models (5a and 5b) using the broader spatial weights (INV and INV_ST) and the less precise measure of general deterrence (STACT), but insignificant and occasionally negative in the other models. This is consistent with the results of Table 4, where the observed variables from a non-spatial model explained much of the spatial correlation in compliance.

Applying spatial econometric techniques does not greatly affect the coefficients on the other variables in the model, as can be seen by comparing coefficients in Table 5 to those in Table 2. The significance levels on other explanatory variables in the spatial model are similar to, or even a bit larger than, those found in the non-spatial model. This is most noticeable for the regulatory enforcement measures. The specific deterrence effect (INSPECT) is at least borderline significant in all models. The INSPNB and INSPNBOUT measures of general deterrence both gain significance with the INV_ST_SIC weight matrix. Some of the plant characteristics also gain in significance. On the whole, including the spatially lagged dependent variable in the analysis strengthens rather than weakens the importance of the other explanatory variables in the model.

Consider the regulatory variables in more detail, focusing on model 5f, which includes the most spatially detailed regulatory measures. First, which is more important, specific deterrence (INSPECT) or general deterrence (INSPNB)? The INSPECT coefficient is roughly ten times larger than that of INSPNB (0.183 versus 0.015), but the mean of INSPECT is only one-fortieth that of INSPNB (0.48 versus 18.96). This suggests that the overall effect of regulation through general deterrence (mean $\times$ coefficient of INSPNB) could be at least as important as its effect through specific deterrence, similar to results for OSHA enforcement in Scholz and Gray (1990).

Turning to the importance of jurisdictional boundaries for regulatory analyses, the negative sign on INSPNBOUT shows that inspections on plants in neighboring states are not as effective at improving compliance. In fact, the negative coefficient on INSPNBOUT is larger in magnitude than the positive one on INSPNB, so increased inspections at plants in neighboring states would be predicted to reduce a plant's compliance, although this effect is not statistically significant. One possible explanation is that state regulators, concerned about other trouble spots in their own state, do not bother putting much effort into areas near "clean" borders (where neighboring regulators are pressuring the plants on their side of the border to reduce pollution) — a sort of cross-border substitution of regulatory intensity.

We carry out similar analyses for the toxic release and air emissions measures in Table 6. The RHO term shows insignificant effects for spatially lagged performance, consistent with the spatial correlation results in Table 4. As we found earlier for the non-spatial models in Table 3, the other explanatory variables are generally insignificant, and we see a similar pattern of signs between the spatial and non-spatial models of emissions.

TABLE 6: Spatially-Lagged Models of Air Emissions (*t*-Statistics in Parentheses)

DEPVAR WEIGHT	6a AIRTOX INV	6b AIRTOX INV_ST	6c $PM_{2.5}$ INV	6d $PM_{2.5}$ INV_ST	6e SO_2 INV	6f SO_2 INV_ST
RHO	−0.026	−0.029	−0.029	−0.032	−0.033	−0.035
	(−1.509)	(−1.674)	(−0.646)	(−0.714)	(−0.693)	(−0.735)
INSPECT	0.210	0.219	0.081	0.081	5.896	5.899
	(0.306)	(0.320)	(0.879)	(0.882)	(2.551)	(2.553)
INSPNB	0.149	0.156	0.000	0.000	0.081	0.083
	(2.853)	(2.934)	(0.013)	(0.041)	(0.352)	(0.358)
INSPNBOUT	−0.030	−0.050	0.003	0.003	−0.143	−0.144
	(−0.325)	(−0.544)	(0.223)	(0.204)	(−0.383)	(−0.387)
LPROD	2.139	2.113	0.073	0.072	1.013	0.995
	(1.428)	(1.411)	(0.365)	(0.360)	(0.200)	(0.197)
AGE	0.013	0.014	0.011	0.011	0.057	0.057
	(0.463)	(0.473)	(3.192)	(3.191)	(0.659)	(0.660)
SIZE	−2.346	−2.352	−0.099	−0.099	−3.921	−3.920
	(−5.035)	(−5.053)	(−1.609)	(−1.611)	(−2.525)	(−2.525)
DIRTYSIC	−2.521	−2.522	−0.043	−0.043	−0.854	−0.853
	(−2.032)	(−2.034)	(−0.236)	(−0.234)	(−0.184)	(−0.184)
PAOC	−0.269	−0.274	0.014	0.014	−0.707	−0.707
	(−0.682)	(−0.693)	(0.169)	(0.168)	(−0.330)	(−0.330)
POOR	−0.047	−0.045	−0.031	−0.031	0.165	0.164
	(−0.181)	(−0.174)	(−0.831)	(−0.838)	(0.177)	(0.176)
MINORITY	−0.010	−0.014	0.009	0.009	0.039	0.039
	(−0.133)	(−0.191)	(0.876)	(0.880)	(0.153)	(0.154)
ELDERS	0.128	0.134	−0.003	−0.002	1.229	1.240
	(0.315)	(0.328)	(−0.047)	(−0.034)	(0.800)	(0.807)
KIDS	0.032	0.054	0.051	0.050	2.083	2.087
	(0.032)	(0.055)	(0.270)	(0.268)	(0.440)	(0.440)
BORDER	1.523	1.462	−0.161	−0.161	−1.100	−1.100
	(1.039)	(0.998)	(−0.782)	(−0.780)	(−0.213)	(−0.213)
ENVSPEND	−0.239	−0.239	−0.002	−0.002	−0.296	−0.300
	(−1.318)	(−1.320)	(−0.072)	(−0.074)	(−0.514)	(−0.520)
DEMOCRAT	−16.890	−16.772	1.954	1.948	3.434	3.255
	(−2.063)	(−2.049)	(1.473)	(1.469)	(0.102)	(0.097)
TURNOUT	10.075	10.177	−1.115	−1.056	−11.021	−10.565
	(1.158)	(1.171)	(−0.617)	(−0.582)	(−0.243)	(−0.233)
_R^2	0.177	0.179	0.203	0.203	0.188	0.188
_Log-L	−969.75	−978.31	−63.276	−63.268	−392.48	−392.40

Note: Estimates are based on observations of 299 plants in 1997 for toxic air pollutants (AIRTOX, models 6a and 6b), and 102 plants in 1996 for conventional air pollutants (SO_2 and $PM_{2.5}$), using a spatially lagged regression analysis. RHO is the estimated autoregressive coefficient, as in Equation (5). Two different spatial weighting matrices are considered: INV = (1/distance) and INV_ST = (1/distance) restricted to plants in the same state.

6. CONCLUSIONS

We incorporate a variety of spatial components in our models of plant-specific environmental performance (measured by air pollution compliance, conventional air emissions, and toxic releases). We create explanatory variables based on the plant's location, test for spatial correlation in environmental performance and the explanatory variables, and examine whether spatial patterns in the explanatory variables can explain spatial patterns in the dependent variables (performance). We then explicitly model the spatial component of environmental performance using a structural spatial dependencies model, incorporating spatially lagged dependent variables. Finally, we compare the results of spatial and non-spatial models to see how including spatial effects influences the estimated impact of different explanatory variables.

A large amount of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, more pollution-abatement-intensive plants, and those in single-plant firms, having lower compliance levels. Some local demographic characteristics matter — having more elderly or minority residents nearby is associated with somewhat greater compliance rates — but political measures show little impact on compliance. The effects of inspection activity tend to have the expected signs, but are not always significant. Having more inspections at the plant, at nearby plants and at plants in the same state is associated with greater compliance. The comparison of coefficients and means for the measures of general and specific deterrence effects suggests that general deterrence is at least as important as specific deterrence. Inspections at nearby plants in other states do not seem to increase compliance, confirming the importance of recognizing borders when modeling the impact of regulatory activity on compliance.

Our spatial analysis indicates significant positive spatial correlations in compliance: plants located near each other tend to have similar compliance rates. In addition, this effect does not cross state borders — only plants in the same state behave similarly — reinforcing the importance of jurisdictional boundaries in a federal regulatory system where most of the enforcement activity is done by state regulators. The explanatory variables in our models also show positive spatial correlations: nearby plants are similar in terms of size, productivity, age, and abatement expenditures, and these effects do carry across state borders. Spatial patterns in explanatory variables appear to explain a sizable fraction of the spatial patterns in compliance, as the residuals from some compliance models show less than half the spatial correlation of the original compliance measures. Models which explicitly incorporate spatially lagged compliance status in the estimation find rather small effects, but their inclusion raises the significance level of some of the other spatially explicit explanatory variables in the models, including measures of regulatory activity.

Our findings of significant spatial effects for compliance status do not carry over to our other measures of environmental performance — emissions of conventional and toxic air pollutants. In fact, few variables we tested had significant impacts on either toxic releases or conventional air emissions. This may be partially due to the smaller samples of plants with toxic release or conventional air emissions data. It may also be due to the heterogeneity of the plants included in the analysis. Unlike most prior research, we include plants from all manufacturing industries in our analysis, rather than focusing on a specific industry. This was necessary to get enough plants close enough together to do spatial analyses, but the different processes determining pollution intensities for plants in different industries may make it problematic to estimate a single equation covering all plants. Compliance effects may be less industry-specific, and hence easier to estimate. Being a binary variable, compliance does not exhibit as great a variation in range across industries, which may also help the estimation.

Thus, our overall results indicate a significant, but limited, role for explicitly including spatial factors when modeling environmental performance. Our future research plans include a wider testing of alternative specifications of the spatial effects, to see how robust our conclusions are to different spatial weighting matrices and different sets of explanatory variables. We also hope to expand the analysis to include panel data on both air and water pollution performance, as well as expanding the dataset to include plants near additional cities. This will help us provide a richer picture of the spatial correlations in compliance across plants, and may increase our ability to explain what causes those correlations.

REFERENCES

Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models*, Dordrecht: Kluwer Academic Publishers.

Anselin, Luc, and Sergio J. Rey. 1991. "Properties of Tests of Spatial Dependence in Linear Regression Models," *Geographical Analysis*, 23, 112–131.

Arora, Seema, and Timothy N. Cason. 1999. "Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxic Release Inventory," *Southern Economic Journal*, 65, 691–716.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 76, 169–217.

Gray, Wayne B., and Mary E. Deily. 1996. "Compliance and Enforcement: Air Pollution Regulation in the U.S. Steel Industry," *Journal of Environmental Economics and Management*, 31, 96–111.

Gray, Wayne B., and Ronald J. Shadbegian. 2004. "Optimal Pollution Abatement — Whose Benefits Matter and How Much?," *Journal of Environmental Economics and Management*, 47, 510–534.

Gray, Wayne B., and Ronald J. Shadbegian. 2005. "When and Why Do Plants Comply? Paper Mills in the 1980s," *Law and Policy*, 27, 238–261.

Hamilton, James. 1993. "Politics and Social Costs: Estimating the Impact of Collective Action on Hazardous Waste Facilities," *Rand Journal of Economics*, 24, 101–125.

Hamilton, James. 1995. "Testing for Environmental Racism: Prejudice, Profits, Political Power?" *Journal of Policy Analysis and Management*, 14, 107–132.

Harrington, Winston. 1988. "Enforcement Leverage when Penalties are Restricted," *Journal of Public Economics*, 37, 29–53.

Helland, Eric A. 1998. "The Enforcement of Pollution Control Laws: Inspections, Violations, and Self Reporting," *Review of Economics and Statistics*, 80, 141–153.

Helland, Eric A. 2003. "Pollution Incidence and Political Jurisdiction: Evidence from the TRI," *Journal of Environmental Economics and Management*, 46, 403–424.

Henderson, J. Vernon. 1999. "Marshall's Economies," Working Paper No. 7358, National Bureau of Economic Research.

Kahn, Matthew E. 1999. "The Silver Lining of Rust Belt Manufacturing Decline," *Journal of Urban Economics*, 46, 360–376.

Laplante, Benoit and Paul Rilstone. 1996. "Environmental Inspections and Emissions of the Pulp and Paper Industry in Quebec," *Journal of Environmental Economics and Management*, 31, 19–36.

LeSage, James P. 1999. Spatial Econometrics, available at http://www.spatial-econometrics.com.

LeSage, James P. 2000. "Bayesian Estimation of Limited Dependent Variable Spatial Autoregressive Models," *Geographical Analysis*, 32, 19–35.

Magat, Wesley A., and W. Kip Viscusi. 1990. "Effectiveness of the EPA's Regulatory Enforcement: The Case of Industrial Effluent Standards," *Journal of Law and Economics*, 33, 331–360.

Manski, Charles F. 2000. "Economic Analysis of Social Interactions", *The Journal of Economic Perspectives*, 14, 115–136

McGuckin, Robert H., and George A. Pascoe. 1988. "The Longitudinal Research Database: Status and Research Possibilities," *Survey of Current Business*, 68, 30–37.

Nadeau, Louis W. 1997. "EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance," *Journal of Environmental Economics and Management*, 34, 54–78.

Scholz, John T., and Wayne B. Gray. 1990. "OSHA Enforcement and Workplace Injuries: A Behavioral Approach to Risk Assessment," *Journal of Risk and Uncertainty*, 3, 283–305.

Shadbegian, Ronald J. and Wayne B. Gray. 2003. "What Determines the Environmental Performance of Paper Mills? The Roles of Abatement Spending, Regulation, and Efficiency," *Topics in Economic Analysis & Policy*, 3, http://www.bepress.com/bejeap/topics/vol3/iss1/art15.

Shimshack, Jay P. and Michael B. Ward. 2005. "Regulator reputation, enforcement, and environmental compliance," *Journal of Environmental Economics and Management*, 50, 519–540.

Sigman, Hilary 2002. "International Spillovers and Water Quality in Rivers: Do Countries Free Ride?," *American Economic Review*, 92, 1152–1159.

Sigman, Hilary. 2004. "Transboundary Spillovers and Decentralization of Environmental Policies," *Journal of Environmental Economics and Management*, 50, 82–101.